

**AN IMPROVED MULTIPLE CLASSIFIER COMBINATION SCHEME
FOR PATTERN CLASSIFICATION**

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Abstrak

Gabungan pengelas berganda dianggap sebagai satu arah baru dalam bidang pengecaman corak untuk meningkatkan prestasi pengelasan. Ketiadaan garis panduan piawai untuk membangunkan pengelas gabung yang tepat dan pelbagai merupakan masalah utama dalam gabungan pengelas berganda. Ini adalah kerana kesukaran untuk mengenal pasti jumlah pengelas homogen dan bagaimana menggabungkan hasil pengelas. Kaedah gabung yang paling biasa digunakan ialah strategi rawak manakala teknik pengundian terbanyak digunakan sebagai penggabung pengelas. Walau bagaimanapun, strategi rawak tidak dapat menentukan bilangan pengelas dan pengundian terbanyak tidak mempertimbangkan kekuatan setiap pengelas, sehingga menyebabkan ketepatan pengelasan yang rendah. Dalam kajian ini, satu skim gabungan pengelas berganda yang lebih baik dicadangkan. Algoritma *ant system* (AS) digunakan untuk melakukan sesekat set ciri dalam pembentukan subset ciri yang mewakili pengelas. Satu ukuran kekompakan diperkenalkan sebagai satu parameter dalam membina pengelas gabung yang tepat dan beragam. Satu kaedah mengundi pemberat digunakan untuk menggabungkan hasil pengelas dengan mempertimbangkan kekuatan pengelas sebelum pengundian dilakukan. Eksperimen telah dijalankan menggunakan empat pengelas asas iaitu *nearest mean classifier* (NMC), *naive bayes classifier* (NBC), *k-nearest neighbour* (*k*-NN) dan *linear discriminant analysis* (LDA) ke atas set data penanda aras, untuk menguji kredibiliti skim gabungan pengelas berganda yang dicadangkan. Purata ketepatan pengelas gabung homogen NMC, NBC, *k*-NN dan LDA adalah 97,91 %, 98,06 %, 98,09 % dan 98,12 %. Ketepatan adalah lebih tinggi daripada yang diperolehi melalui penggunaan kaedah lain dalam membangunkan gabungan pengelas berganda. Skim gabungan pengelas berganda yang dicadangkan dapat membantu dalam membangunkan gabungan pengelas berganda untuk pengecaman dan pengelasan corak yang lain.

Kata Kunci: Gabungan pengelas berganda, Ukuran keragaman, Pengecaman dan pengelasan corak, Algoritma *ant system*, Pengundian berberat.

Abstract

Combining multiple classifiers are considered as a new direction in the pattern recognition to improve classification performance. The main problem of multiple classifier combination is that there is no standard guideline for constructing an accurate and diverse classifier ensemble. This is due to the difficulty in identifying the number of homogeneous classifiers and how to combine the classifier outputs. The most commonly used ensemble method is the random strategy while the majority voting technique is used as the combiner. However, the random strategy cannot determine the number of classifiers and the majority voting technique does not consider the strength of each classifier, thus resulting in low classification accuracy. In this study, an improved multiple classifier combination scheme is proposed. The ant system (AS) algorithm is used to partition feature set in developing feature subsets which represent the number of classifiers. A compactness measure is introduced as a parameter in constructing an accurate and diverse classifier ensemble. A weighted voting technique is used to combine the classifier outputs by considering the strength of the classifiers prior to voting. Experiments were performed using four base classifiers, which are Nearest Mean Classifier (NMC), Naive Bayes Classifier (NBC), k -Nearest Neighbour (k -NN) and Linear Discriminant Analysis (LDA) on benchmark datasets, to test the credibility of the proposed multiple classifier combination scheme. The average classification accuracy of the homogeneous NMC, NBC, k -NN and LDA ensembles are 97.91%, 98.06%, 98.09% and 98.12% respectively. The accuracies are higher than those obtained through the use of other approaches in developing multiple classifier combination. The proposed multiple classifier combination scheme will help to develop other multiple classifier combination for pattern recognition and classification.

Keywords: Multiple classifier combination, Diversity measure, Pattern recognition and classification, Ant system algorithm, Weighted voting.

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List of Abbreviations

ACO	Ant Colony Optimisation
AS	Ant System
ASFSP	Ant System-based Feature Set Partitioning
Bagging	Bootstrap Aggregating
BKS	Behavior Knowledge Space
DECORATE	Diverse Cretion by Oppositional Re-labeling of Artificial Training Examples
DF	Double Fault
DT	Decision Tree
DOG	Decomposed Oblivious Gain
ECOC	Error Correcting Output Codes
GA	Genetic Algorithm
k -NN	k Nearest Neighbour
KW	Kohavi Wolpert
LDA	Linear Discriminant Analysis
MASWOD	maximum of posterior probability average with self-adaptive weight based on output vectors and decision template
MCC	Multiple Classifier Combination
NBC	Naïve Bayes Classifier
NMC	Nearest Mean Classifier
NN	Neural Network
PSO	Particle Swarm Optimisation
RS	Random Subspace
SCP	Set Covering Problem
SPP	Set Partitioning Problem
SVM	Support Vector Machine
UCI	University of California Irvine
WNNE	Weighted Nearest Neighbour Ensemble

CHAPTER ONE

INTRODUCTION

1.1 Background

Pattern classification is the process of classifying patterns into predefined category (or class label) based on their feature set (or attribute set) (Dougherty, 2013). Pattern classification aims to determine pattern categories based on characteristics of the patterns, where the categories have been priorly defined. Classification process is divided into two phases, namely training and testing phases. In the training phase, the pattern sample whose class is known (training object) is used to establish a model. In the testing phase, a model that has been established is tested with the other patterns to determine the model's accuracy (Neelamegam & Ramaraj, 2013). If the accuracy is good, then the model can be used to predict the class of unknown patterns. Figure 1.1 depicts the general framework of classification task.

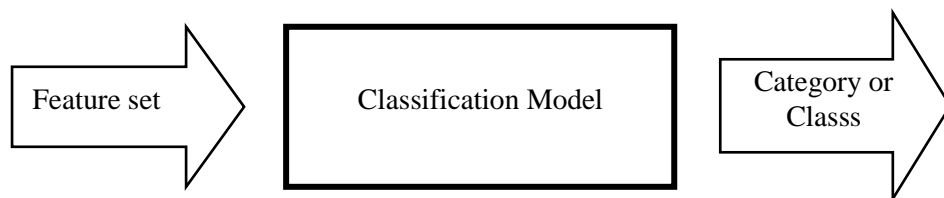


Figure 1.1 Classification task general framework

Pattern classification is an important area in machine learning and artificial intelligence. The impact of poor classification will put the object into the wrong class which may lead to wrong decisions being made, hence causing losses to the recipient or the decision makers.

Classification task is widely used in the decision-making process, for example on pattern recognition (Kaur & Kaur, 2013). Pattern recognition is a discipline in which

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